The Moving Average Crossover strategy: Does it work for the S&P500 Market Index?

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Abstract

The contribution of behavioral finance in the investor's world cannot be fully justified without the existence and use of technical indicators which all are clear indications of investors' representativeness and availability bias. Existing literature on technical analysis based trading systems are abundant where some studies have concluded the use of technical analysis and fundamental analysis techniques in stock trading strategies, with a preference over the former in predicting turning points. This study aims to answer whether an optimized moving average crossover strategy based on daily data outperforms a buy and hold strategy. The paper investigates the use of an optimized moving average crossover strategy for the S&P500, by using the SPDR S&P500 Exchange Traded Fund as a proxy for the US market index. The optimized strategy is evaluated against a buy and hold strategy over the five distinct waves which were witnessed during the 1993-2014 period. The annualized returns, annualized risk and the Sharpe performance measure are used as indicators to compare between the two strategies. Findings tend to support higher absolute returns and risk for the buy-and-hold strategy, particularly during correction waves. When compared to the buy-and-hold strategy over the post financial crisis period, the optimized double cross over strategy resulted in a relatively lower risk and returns. The market timing strategy still outperformed the naïve buy-and-hold strategy, with a relatively higher Sharpe performance measure. Alternatively stated, the rather simple moving average strategy which fits easily in the investor's world due to his or her availability and representativeness bias, is preferred over the buy and hold strategy where the latter requires more effort when bearing the two correction waves witnessed during the 1993-2014 period.

JEL Classification Codes: G11, G15, G17
Keywords: Moving Average Crossovers, Financial Markets, Trading Strategy

Background to Study and Trends in MA Crossovers

Eugene Fama, the 2013 Nobel Prize winner in Economics, stated in Fama (1970) that the market price at any time reflects all information in the market, such that the market is efficient. In short, no investor has an advantage in predicting the return on a stock price because no one has access to information not already available to everyone else. Yet, the investor exhibit biases and use heuristics (rules of thumb) in his decision making process. Tversky and Kahneman (1974) provide a good review of the use of heuristics and biases when making judgment under uncertainty. For instance, Barber and Odean (2011, 2013) find that investors sell winning investments while holding losing investments (disposition effect bias); they are heavily influenced by the past return performance in their purchase decisions (representativeness bias), and tend to hold undiversified portfolios (availability bias). Kahneman (2011) even described that the investor, like any human being, uses two systems – System 1 and 2. System 1 takes all the readily available input and through a wonderful associative process constructs an explanatory "story" which is best fitted based on the WYSIATI principle (What you see is all there is). While System 1 wastes no time constructing alternative hypotheses and testing them, System 2 takes considerable mental effort and considers alternatives. System 1 tends to be the driver between the two systems due to its quick intuitive and less effortful approach.

In the same line of thought, most if not all decisions made in financial markets by investors have considered the use of techniques like fundamental analysis and technical analysis, whether the period of investing is for a short time or long period, or whether it is an active or passive trading strategy. For instance, Dimson et *al.* (2002) showed that many global asset classes in the twentieth century produced spectacular gains in wealth for individuals who bought and held those assets for generation-long holding periods, but the assets also went through regular and painful draw downs like 2008. All of the G-7 countries have experienced at least one period where stocks lost 75% of their value. Conversely, Faber (2013) found that, using an out-sampling testing comparison between a timing model and a buy-and-hold strategy from 2006-2012, the timing strategy beat the buy and hold by over two percentage points per year, with much less volatility and most importantly to many investors, lower draw downs.

Taylor and Allen (2002), after conducting a survey with chief foreign exchange dealers in the UK, found that 90 percent of respondents placed some weight on technical analysis, with a skew towards relying on technical analysis as opposed to fundamental analysis. Similarly, Lui and Mole (1998), after conducting a survey with foreign dealers in Hong Kong, found that technical analysis is considered slightly more useful in forecasting trends than fundamental analysis, but significantly more useful in predicting turning points. More importantly, moving average (MA) and/or other trend-following systems are the most useful technical technique. One of the main reasons such tools are used widely is due to the fact that people adjust less by staying close to their anchors (here being the investment tools they used more frequently) as proposed in Epley and Gilovich (2006), where they confirmed that adjustment to other techniques is indeed an effortful operation.

While existing literature about the success of trend following systems is abundant, Zweig and Goldfischer (1986) and Hayes (2000) provide a good review of pioneer systems like the Dow Theory, which upon which today's Dow Jones Industrial Average is based from. The existence of technical analysis based systems, with particular reference to the moving average, can be traced back to Tintner (1935) and Cowles (1933). Perhaps the most cited long term measurement of trend among technical analysts is the 200 day MA. Spiegel (2013), using a percentage price oscillator approach with 1% up and down variation, testing the long run MA on the Dow Jones Industrial Average (DJIA) over the 1886-2006 period, and found the market timing strategy to outperform a buy-and-hold strategy. Similar results were held for the Nasdaq Composite Index. Overall, the use of the MA technique resulted in annual excess return of 4% (adjusted for transaction costs) with 25% less volatility, when comparing the market timing and buy and hold strategies. Using a similar approach, Faber (2013) tested the a 10 month MA for the S&P500 market index over the 1901-2012 period and found the market timing strategy to outperform a buy-and-hold of the index in terms of returns, volatility and Sharpe performance measurements. The use of the MA strategy had fewer instances of both large gains and large losses, with correspondingly higher occurrences of small gains and losses. Basically, the technical analysis tool signalled when an investor should be long a riskier asset class (equity) with upside potentials, and when to be out and sitting in cash (lower risk asset class). Alternatively stated, the MA strategy avoids the far left tail of big losses while sacrificing the far right tail of big gains.

A popular use for moving averages is to develop simple trading systems based on moving average crossovers. A trading system using two moving averages would give a buy signal when the shorter (faster) moving average advances above the longer (slower) moving average. A sell signal would be given when the shorter moving average crosses below the longer moving average. The speed of the systems and the number of signals generated will depend on the length of the moving averages. Shorter moving average systems will be faster, generate more signals and be more prone for early entry. However, they will also generate more false signals than systems with longer moving averages. The aim of this paper is to test the use of an optimized moving average crossover trading strategy for the S&P500 market index. This paper will also help to shed light whether there is a unique moving average crossover strategy which works across time. The optimized strategy is benchmarked against a buy-and-hold strategy as part of robustness testing. The rest of the paper provides some background to the study, lays the framework on the data and research methodology, conducts the analysis, before ending with some conclusive remarks.

Data and Research Methodology

Data Assumptions:

1. All entry and exit prices are on the day of the signal at the close.
2. The frequency of data is set initially to daily.
3. The effect of discounts due to bulk trading and taxes are ignored.
4. All orders occur at market prices. Limit and stop order options are not allowed at this stage.

Assumption 2 will be robust tested in the later part of the paper as part of optimizing the model. The risk and return of the MA based strategy model would be compared with a simple buy-and-hold strategy of the S&P500 market index. The SPDR S&P500 ETF (NYSEARCA: SPY), an exchange-traded fund (ETF) incorporated in the USA, which replicates the yield performance of the S&P500 Index, would be used as the data for the S&P500. The ETF Trust consists of a portfolio representing all 500 stocks in the S&P 500 Index. It holds predominantly large-cap U.S. stocks and the holdings are weighted by market capitalization.

Annualized return and annualized standard deviation of daily returns would be used as measurements of risk and return. The Sharpe ratio would then be used to compare the performance of the MA based strategy with the buy-and-hold strategy. The time window under analysis is set from 1st February 1993 to 22nd November 2014, to be in line with the inception date of the ETF which was 22nd January 1993. In regards to Assumption 3, Wilcox and Crittenden (2005) argue that trend following systems still work well in the equities market after adjusting for taxes. Further, it is expected in this current paper, that any optimized strategy based on moving averages of shorter durations would result in more trading transactions, creating sufficient losses for the investor to benefit from during taxation times. Further, more transactions would result in more discounts from the trading platforms offered by brokers. Assumption 4 is maintained at this stage to prevent any subjectivity from the trader's beliefs what about are the boundaries of prices that could be entered as limit or stop orders.

Annualized risk and return

$$Annualized\ Return = \{(1 + r_z)(1 + r_{z+1}) \dots * (1 + r_n)\}^{365/t} - 1 \qquad (1)$$

$$Annualized\ risk = Daily\ \sigma_t . \sqrt{365} \qquad (2)$$

where t represents the number of days the investment is held. 365 days is used to be in line with 1 year where trading can take place all year round through market makers compared with stock exchanges which will trade, on average, on a 260 trading days per year.

The Moving Average (MA)

Used predominantly to smooth noisy data, MA involves partitioning the original data into overlapping sets of a given sample size, typically by shifting along one step at a time. The new smoothed data is made by computing the average for each of the sets. Larger sample sizes result in greater smoothing. Given a sequence (series of numbers), $\{a_i\}_{i=1}^{N}$, the ***n***-moving average (S_i) of the series of numbers can be defined by taking the arithmetic mean of subsequences of *n* terms,

$$S_i = \frac{1}{n} \sum_{j=i}^{i+n-1} a_j \tag{3}$$

So the sequences S_n giving n-moving averages are

$$S_2 = \frac{1}{2}\,(a_1 + a_2, a_2 + a_3, a_3 + a_4, \ldots., a_{n-1} + a_n)$$

$$S_3 = \frac{1}{3}\,(a_1 + a_2 + a_3, a_2 + a_3 + a_4, a_3 + a_4 + a_5, \ldots., a_{n-2} + a_{n-1} + a_n)$$

For example Pair wise Moving Average $[\{a_1, a_2, a_3, a_4, a_5\}, 2] = \left\{\frac{a_1+a_2}{2}, \frac{a_2+a_3}{2}, \frac{a_3+a_4}{2}, \frac{a_4+a_5}{2}\right\}$

The direction of the moving average conveys important information about prices. A rising moving average shows that prices are generally increasing. A falling moving average indicates that prices, on average, are falling. A rising long-term moving average reflects a long-term uptrend. A falling long-term moving average reflects a long-term downtrend.

What happens if *n* is increased/ decreased?

If ***n***, which represents the number of periods, is increased, the latest data added in the calculation would tend to have a subdued effect on the moving average calculation. This would result in greater smoothing of the moving average data series. Conversely, if *n* is decreased, the effect of the latest data added would tend to be more significant. The length of the moving average depends on the analytical objectives. Short moving averages (5-20 periods) are best suited for short-term trends and trading. Chartists interested in medium-term trends would opt for longer moving averages that might extend 20-60 periods. Long-term investors will prefer moving averages with 100 or more periods.

Figure 1 provides five panels (A-E) with Panel A showing the daily MA for 14 days, Panel B with the daily MA for 50 days, Panel C with the daily MA for 100 days, Panel D with the daily MA for 200 days, and Panel E with a 1000 day MA. It can be observed that a 14 day MA tracks the ETF prices more closely than a 200 or 1000 day MA. Alternatively stated, a 1 day MA would almost perfectly reflect the more volatile and everyday stock prices while a longer period MA, say 100, would be flatter and represent a long-run and more stable state of the underlying asset.

While the number of periods is important, the frequency in the data interval is also critical in determining the behavior of the MA dataset, whether the interval is daily, weekly, monthly or quarterly. Figure 2 provides several plots the SPDR ETF using varying moving averages periods for February 1993- November 2014. The black curves represent the ETF prices, while the red ones represent MA curves. Panel A provides a 14 period day MA, Panel B with a 14 period weekly MA, Panel C with a 14 period Monthly MA, and Panel D with a 14 period Quarterly MA. It can be observed that a daily MA tracks the ETF prices more closely, compared to a higher data interval like the monthly or quarterly series. The quarterly interval MA series is less prone to the daily fluctuations of the prices, which is in line with the findings from Figure 1, where a longer time period resulted in a smoother MA dataset.

Figure 1 MA with varying periods

Panel A: Daily MA (14)

Panel B: Daily MA (50)

Panel C: Daily MA (100)

Panel D: Daily MA (200)

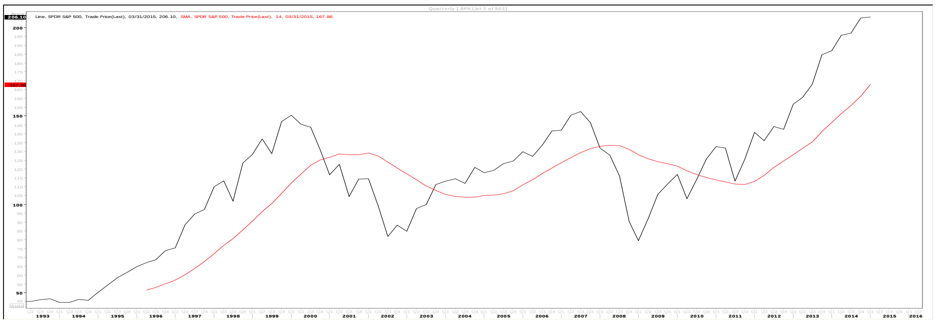
Panel E: Daily MA (1000)

Figure 2 Moving Averages (14 periods)

Panel A: 14 Periods MA (Daily)

Panel B: 14 Periods MA (Weekly)

Panel C: 14 Periods MA (Monthly)



Panel D: 14 Periods MA (Quarterly)

Double Crossover Strategy

Covered extensively by Murphy (1999), double crossovers involve one relatively short moving average and one relatively long moving average. As with all moving averages, the general length of the moving average defines the timeframe for the system. A system using a 5-day SMA and 35-day SMA would be deemed short-term. A system using a 50-day SMA and 200-day SMA would be deemed medium-term, perhaps even long-term. A bullish crossover occurs when the shorter moving average crosses above the longer moving average. This is also known as a golden cross. A bearish crossover occurs when the shorter moving average crosses below the longer moving average. This is known as a dead cross. Wallstreetcourier (2014) found that although a negative crossover signal does not necessarily lead to significant and longer lasting bear markets, most crossover signals lead to reduction in draw-downs compared to buy and hold strategy.

It is critical to note that moving average crossovers also produce relatively late signals. The longer the moving average periods, the greater is the lag in the signals. These signals work great when a strong trend persists. Alternatively, a moving average crossover system will produce lots of whipsaws, which might result in false signals and cumulative losses. There is also a triple crossover method that involves three moving averages where a signal is generated when the shortest moving average crosses the two longer moving averages. A simple triple crossover system might involve 5-day, 10-day and 20-day moving averages. To reduce the effect of late signals, technical analysts can use tools such as Double Exponential Moving Averages (DEMA) where the exponential moving average error to the value is added to the exponential moving average of the stock price, thereby reducing false signals and enables the investor to get into a trend sooner (Mulloy, 1994). The scope of this paper will focus primarily on the double cross over strategy. The use of filters such as MACD (Moving Average Converging Diverging Oscillators) (with Centerline crossovers) and PPO (Percentage Price Oscillators) can be integrated as future research avenues.

Areas of testing under study:

1. Does a MA (θ) cross-over MA (β) result in profits/losses over a defined trading period, where $\theta<\beta$, where θ and β represent days in the moving average formulation?

2. Does an optimized MA strategy, based on daily data intervals outperform/ underperform a buy-and-hold strategy in the post financial crisis period?

Analysis

Figure 3 shows the performance of the S&P500 Market Index and the SPDR S&P500 ETF over the period 1st Feb 1993 – 22nd November 2014. It is important to note that they performed exactly since the ETF product is meant to track the market index. Until 2000, any investor who would have invested from the inception of the ETF would have gained 245%, over an investment period of 91 months. For the next 25 months however, the same investor would have lost 46% of his portfolio value. By the start of 2003, the market picked up again for 61 months, yielding a gain of 90%. Note that the index level topped around 1540 which is roughly near the 1517 level reached in 2000 before the big drop of 46%. During 2007 the market index fell by 52% during the latest global financial crisis and last for 16 months, where it reached its lowest. Note again that this level is less than 100 points away from the 815 level reached in 2002. The market ultimately recovered with a gain of 181% and has lasted 69 months up till now. An investor who would have withstood those fluctuations over the 21 years would have ended with a 371% gain overall, based on the price changes of the ETF alone. Alternatively stated, a buy and hold strategy over those 21 years would have still yielded roughly 370% price gain for the ETF investment.

Figure 3 Performance of the S&P500 Market Index and SPDR S&P500 ETF (1993-2014)

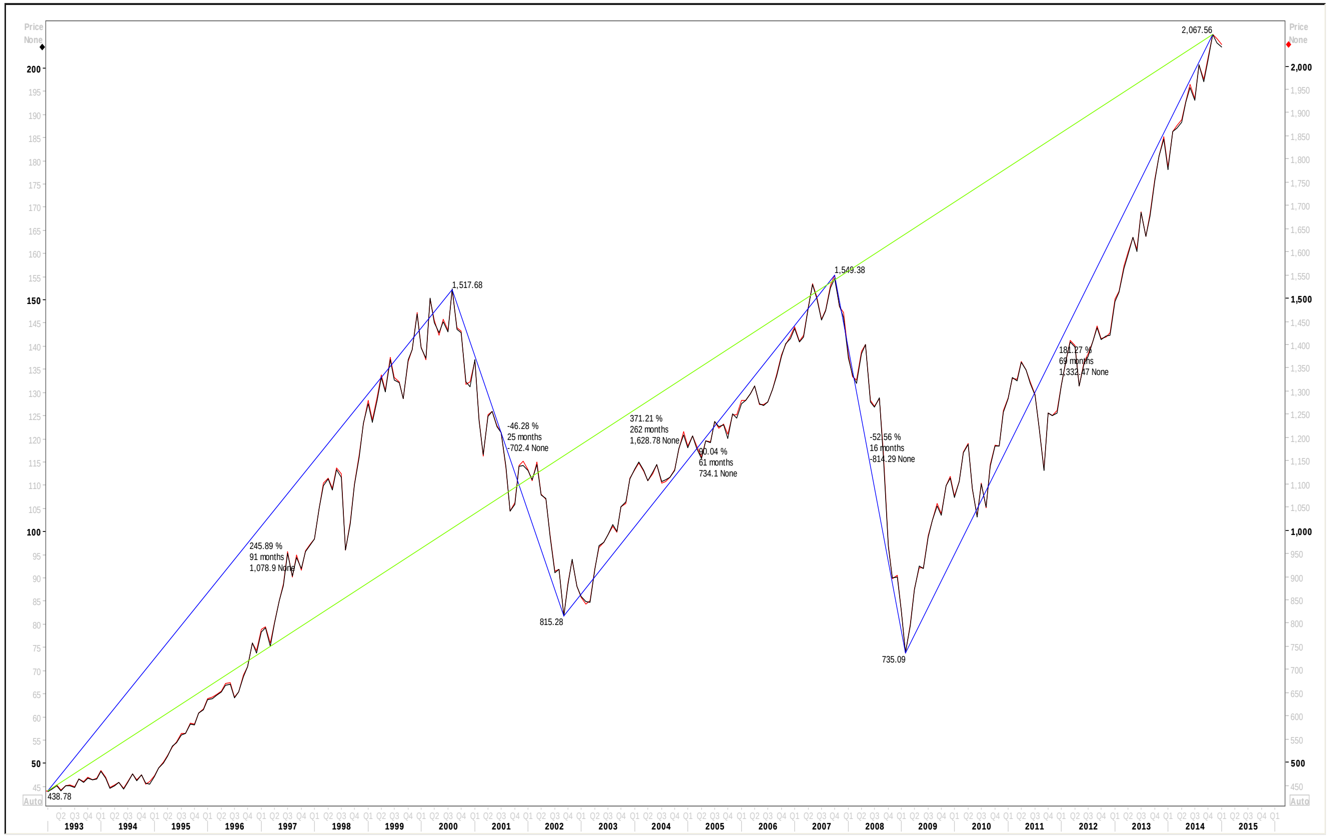
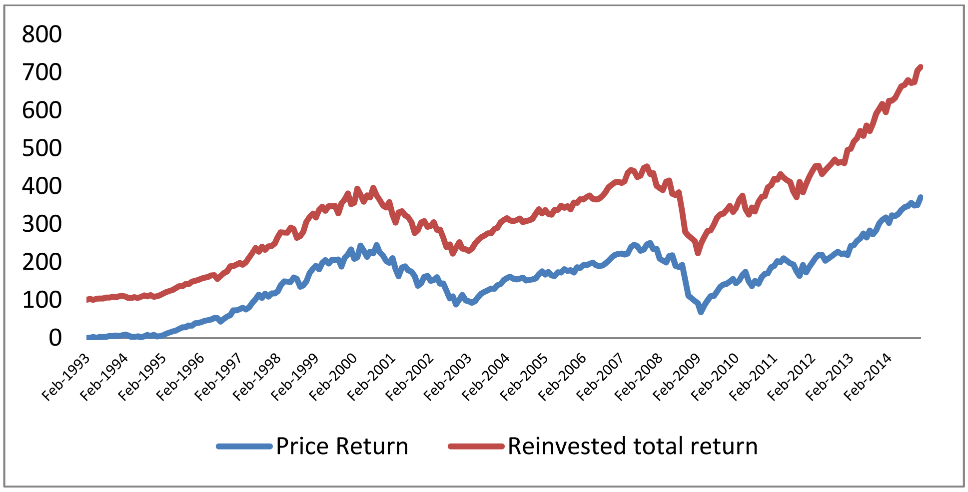


Figure 4 SPY Price Return and Reinvested Total Return (%) (1993-2014)



While Figure 3 shows that the price return was about 371% for the whole period, some investors might be interested to know the reinvested total return of their investments. The difference between the two lines from Figure 4 can be explained due to the fact that the return made on an ETF investment is comprised of two parts. The first component is based on the change in the ETF price, where it can go up and down. The second component is based on the distributions that the ETF may have made. Those distributions represent interest and dividend income on the securities held in the portfolio, as well as capital gains or losses from any securities the fund has sold. The relatively steeper graphs from 2012 onwards can be attributed to the ETF distributing a relatively higher proportion of dividends relative to the securities prices held in the ETF portfolio.

Performance measurement

Buy and Hold Strategy **-** To be able to compare the performance of both a buy and hold strategy and one relying on a MA strategy, the Sharpe performance measurement tool is used. For consistency and comparability purpose, the average of the US 30 year Treasury bonds yields is used for the 1st February 1993 – 22nd November 2014 period. The calculated average treasury yield was 5.114%. The analysis is broken down into the 5 distinct waves as observed from Figure 3. The risk and return are calculated using equations (1) and (2). Table 1 provides the Sharpe measurement results.

Table 1 Annualized Risk and Return of a Buy and Hold Strategy over the full period

	Wave	Annualized Return (%)	Annualized Risk (%)	Sharpe ratio
1 Feb 1993 - 31 Aug 2000	1	22.0%	19%	0.884
1 Feb 1993 - 22 Sep 2002	1+2	8.6%	21%	0.169
1 Feb 1993 - 30 Oct 2007	1+2+3	11.5%	20%	0.323
1 Feb 1993 - 28 Feb 2009	1+2+3+4	4.2%	23%	-0.039
1 Feb 1993 - 22 Nov 2014	1+2+3+4+5	9.8%	22%	0.211

Table 1 provides a breakdown of the annualized return, annualized risk and Sharpe measure for a buy and hold strategy over the 1993-2014 period. Assuming that an investor reinvests the amount at any point in time into his/her portfolio following an increase or decrease in the portfolio value, the portfolio would have witnessed 5 clear waves as mentioned in Table 1. While waves 1, 3 and 5 are up trending, waves 2 and 4 are corrections waves. The 5 waves together form a bullish trend over the whole period. Following the complete market cycle proposed by Frost and Pretcher (1978), this 5 wave move suggests either the end of a bullish cycle, or that these 5 waves are just one wave of a bigger bullish trend. The former suggestion is more likely due to the time period under consideration. It is important to note that, while the annualized returns for all the periods remained positive, it dropped significantly during the correction wave 2. The annualized risk, whether in an uptrend or downtrend wave remained around 20%. While the annualized return for waves 2 and 3 looks close, the Sharpe ratio improved in the later period, suggesting an improvement in the performance of the financial product in wave 3. Assuming the investor would have reinvested all his gains and held his losses with no withdrawals, he would have made an annualized return of nearly 10% with an annualized risk of 22% over the full period. The Sharpe ratio values amalgamate both risk and return and show that the 1990s would have been the best performing period among the 5 periods, except to wave 1 which witnessed higher returns with lower risk. For later analysis, wave 4 would be used as the pre financial crisis period and wave 5 as the post financial crisis period.

Table 2 Annualized Risk and Return of a Buy and Hold Strategy over different wave periods

	Wave	Annualized Return (%)	Annualized Risk (%)	Sharpe ratio
1 Feb 1993 - 31 Aug 2000	1	22%	19%	0.884
1 Sep 2000 - 22 Sep 2002	2	-32%	27%	-1.360
23 Sep 2002 - 30 Oct 2007	3	18%	17%	0.776
31 Oct 2007 - 28 Feb 2009	4	-54%	45%	-1.295
01 Mar 2009 - 22 Nov 2014	5	30%	21%	1.214
1 Feb 1993 - 22 Nov 2014	1-5 combined	9.8%	22%	0.211

While Table 1 is based on the assumption that the investor adopts a buy and hold strategy over the full period, it is also worth analyzing the effect of buy and hold over each of the waves. Due to the fact that waves 2 and 4 are down trending waves, it can be observed from Table 2 that the annualized return was -32% and -54%, accompanied by the highest annualized risk of 27% and 45%. This resulted in negative Sharpe measures, where the excess returns were negative. It is also important to note that the market recovery during the March 2009 - Nov 2014 period resulted in a higher annualized return compared to the bullish trend of the 1990s. The higher returns can be explained due to the fact that investors were bearing a higher risk than the 1990s.

Double Crossover Strategy – Using this strategy requires two moving average series, MA (θ) and MA (β), where θ and β represent a given number of periods, using daily data intervals initially, and $\theta < \beta$. Hence, MA (θ) and MA (β) represent the fast and slow moving averages. A buying strategy occurs when the MA (θ) series crosses over MA (β) and a selling strategy when the MA (θ) series crosses under MA (β). Figure 5 illustrates the use of MA crossovers using FXCM Marketscope data for the S&P500 market.

Figure 5 MA Crossovers Strategy (1993-2014)

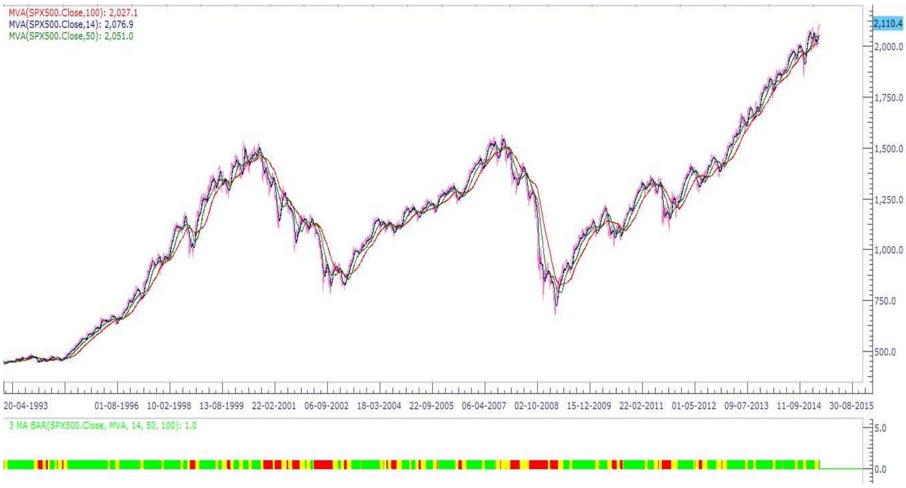


Figure 5 provides a graphical representation of MA (14 days), MA (50 days) and MA (100 days). Due to the period under study being more than 20 years, the use of daily data results in a rather hard to analyze graph. The bottom of the graph helps to alleviate this issue, by providing the green, yellow and red bars. These indicator bars occur based on the following conditions:

Green bar: $\mathrm{MA}(\theta) > MA\ (\beta) > MA\ (\mu)$ (e.g. MA (14) > MA (50) > MA (100))

Red bar: $\mathrm{MA}(\theta) < MA\ (\beta) < MA\ (\mu)$ (e.g. MA (14) < MA (50) < MA (100))

Yellow bar: Any other relationship among the 3 MA series. $\theta < \beta < \mu$.

Importantly, it can be observed that a yellow area is always followed by either a green or red bar and vice versa. While up trending waves 1, 3 and 5 have witnessed mostly green bars, correction waves 2 and 4 have witnessed red bars which support declining prices. While traders would usually follow either a buying or selling strategy when given the green and red signals, the occurrence of more frequent yellow bars usually provided signals of a change in trend in the near future. Due to the lagged nature of MA series, a lot of entry and exit opportunities were missed out. For instance, most of the red bars occurred at the end of both correction waves, when the prices have already dropped significantly. Nonetheless, due to the sufficiently long enough wave periods, any trader who would have gone long (buy) following enough green areas, and shorted (sell) following enough red areas, would have benefited from the crossover strategy. Continuous yellow areas followed by the previous green areas would have been confirmations of an up trending wave direction, while continuous yellow areas followed by the previous red areas would have been confirmations of a down trending wave direction. Continuous yellow areas between green and red areas usually suggested a change towards a new direction. While it might be of interest to analyze the performance of the randomly selected crossover strategy above against a buy and hold strategy, it would be more valuable to the study to optimize the model and then carry a performance evaluation of the optimized model against the buy and hold strategy.

The Optimization Process

Time Frame	Daily
Fast MA criteria	
Minimum value	5
Maximum value	21
Slow MA criteria	
Minimum value	50
Maximum value	200
MA method	Simple Moving Average
Price Type	Close
Close on Opposite	Allowed
Minimum Trade Size	1
Margin Requirement	12%
Bid/Ask spread	0.5

Finance Charges

The broker daily debit or credit interest amounts (rollover) which are based on the total face value of the position. The rollover rates are calculated by referencing the relevant 3 month LIBOR for all index products. Index positions that are open at the close of business on Friday will incur 3 day rollover. For example, if 3 month USD LIBOR is 4.50%, the broker is applying a haircut of +3/-3%, where a long position would cost 7.50%/ 360 per day, whereas a holder of a short position would receive 1.50%/360 per day.

Selection Criteria of the Optimizer

Two common criteria are used:

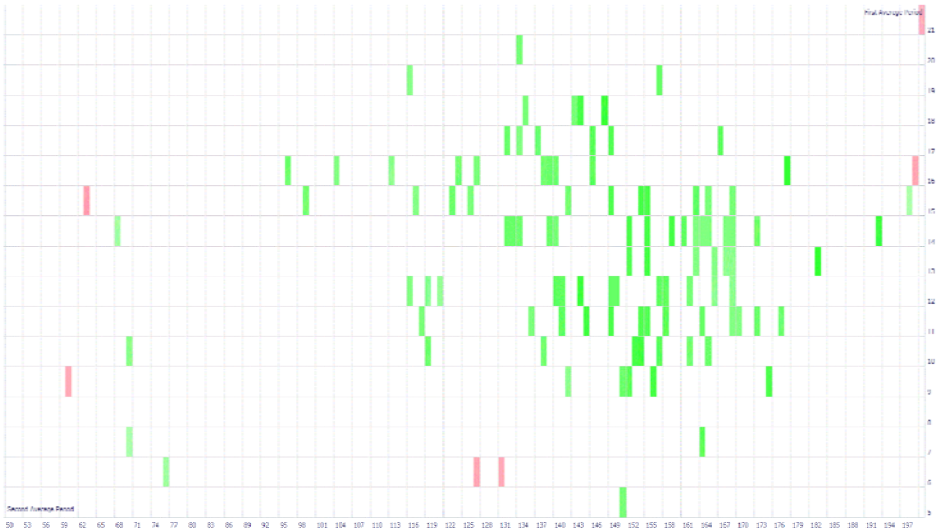
The **Highest balance** will be used to look for the optimized structure set which provides the highest balance of the account at the end.

The **Profit factor** looks for the parameters set which produces more profitable trades than non-profitable. Profit factor is calculated as a ratio of total profit to total loss as follows:

$$Profit\ Factor = Final\ Balance * \frac{Total\ Profit}{Total\ Loss}$$

For the purpose of this study, the highest balance will be used as part of calculating the return and risk. It is important to note that, while part of the profit factor (Total profit/ Total Loss) gives a proxy measurement of risk, standard deviations would be used to be consistent with earlier calculations. Figure 6 provides a heat map which summarizes the optimization results. All possible combinations between the fast and slow MA are back tested, with the fast MA series ranging from 5 to 21 days, and the slow MA series ranging from 50 to 200 days. Darker green slots represent MA cross over combinations with the highest balance. Although not reported here, the top ending balances occurred when the fast MA is between 10 and 20 days and when the slow MA is between 140 and 190 days. The highest balance occurred with a MA (18) and MA (183) cross over strategy, with total profits of $939 and losses of $365, ending with a balance of $100574. This is well below the buy and hold strategy which resulted in nearly 10% annualized return over the full period.

Figure 6 Optimized Results Heat Map



Robustness Testing

While the return made with the cross over strategy tends to be much lesser than with the buy and hold strategy, it is important to analyse the impact of investing with an optimized double cross over strategy. As part of robustness testing, wave 5, which represents mostly the post financial crisis recovery period is analysed in terms of the risk and return using the double cross over strategy. The optimized MA (13,183) model on the ETF prices is back tested using the period 01 March 2009 to 22 November 2014 as time window. Due to the lag effect mentioned earlier in the study, the time window is set to 01 January 2009 in order not to lose any possible early cross overs. Table 4 provides the post financial crisis buying and selling trades which would occur once the MA series cross each other. A buy occurs if the fast MA cross over the slow MA and a sell occurs if the fast MA cross under the slow MA. Any cross over or cross under is immediately followed by reversing the previous trade, and engaging into another reversal trade. For example, as per Table 4, the 1st selling trade which occurred on the 26th May 2010 is closed on the 20th September 2010 by with a long trade, followed by another long trade at $114.21.

Table 3 Post financial crisis cross over transactions

Price	Investment Days	Cross over Date	Buy/Sell
107.17	0	26-May-10	Sell
114.21	114	20-Sep-10	Buy
114.21	114	20-Sep-10	Buy
120.26	314	04-Aug-11	sell
120.26	314	04-Aug-11	sell
128.04	151	05-Jan-12	Buy
128.04	151	05-Jan-12	Buy
139.19	315	20-Nov-12	Sell
139.19	315	20-Nov-12	Sell
142.12	9	29-Nov-12	Buy
142.12	9	29-Nov-12	Buy
186.27	677	16-Oct-14	Sell
186.27	677	16-Oct-14	Sell
198.11	13	29-Oct-14	Buy
198.11	13	29-Oct-14	Buy

To compare the buy and hold strategy with the optimized strategy of wave 5, the Sharpe performance measure is used as an indicator. The optimized strategy yielded a return of 24% over the 1593 investment days, with a risk of 14%. This resulted in a Sharpe of 1.351 for wave 5. Compared with the buy and hold strategy results from Table 2, the cross over strategy ended with both a lower return and lower risk. This is in line with existing literature that the MA strategy tends to result in the avoidance of the far left tail of big losses while sacrificing the far right tail of big gains. Nonetheless, the Sharpe measure under the optimized double cross over strategy is still relatively higher than the buy and hold strategy, suggesting the market timing strategy did outperform a more naïve buy and hold strategy held during wave 5.

Conclusive Remarks

The emergence of behavioral finance can be explained through many facets, including the use of technical analysis techniques such as the moving average. Psychological concepts such as availability bias, WYSIATI and the representativeness bias are all well embedded in the use of historical representations during the time in which investors make decisions, whether informed or not, whether short run or long run. Bearing those neurofinance factors in mind, the aim of this paper was to shed more light if anchoring techniques such as the moving average can work on the S&P500 market index, which represents the top market capitalized firms in the US. This paper initially decomposed a benchmarked buy-and-hold strategy over the 1993-2014 period into 5 distinct waves, and showed that the two correction waves which occurred were accompanied with heightened risk and highest absolute returns compared to the uptrend waves. This is in line with the fact that investors tend to be more agitated with a loss compared to a similar relative gain. Following the construction of an optimized strategy, any investor who would have followed such the market timing strategy, would have ended with relatively lower returns and lower risk than the buy and hold strategy, if he or she has invested in the SPDR ETF product in the post financial crisis period. The Sharpe performance measure which combines both the risk and return variables, shows that the moving average technique is superior to the buy and hold strategy. The reliance of the moving average as a simple anchoring tool which beautifully feeds into our System 1 cannot be ignored. After all, WYSIATI as propelled by Kahneman (2011). While the lag in the simple moving average has been noted in this paper, the use of more sophisticated techniques such as Exponential Moving Average (EMA) or even Double Exponential Moving Average (DEMA) are just techniques which not only are extended versions of the simple moving averages, but which also requires some more mental efforts from the investor. Nonetheless, this study can be further extended to evaluate the impact of optimized cross over strategies, over the different US indices, while also looking at varying the frequency and data intervals in the MA series.

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